Energy Systems, Summer Semester 2023
Lecture 14: Research Topics

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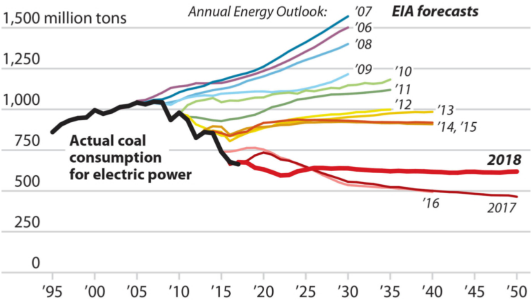
The World is Not a Perfect Optimization Model

We should be skeptical about models and modellers

EIA Coal Consumption Forecasts, 2006-2018

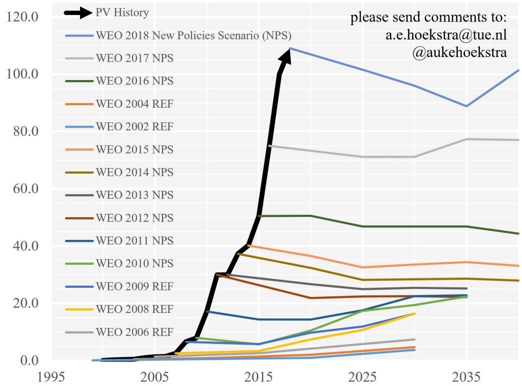
Each year, the Energy Information Administration releases its Annual Energy Outlook, which includes a long-term forecast for U.S. coal consumption for electric power generation. However, the forecasts have been wildly inaccurate, even in the near term.



Source: Energy Information Administration

Annual PV additions: historic data vs IEA WEO predictions

In GW of added capacity per year - source International Energy Agency - World Energy Outlook



We should be skeptical about models and modellers

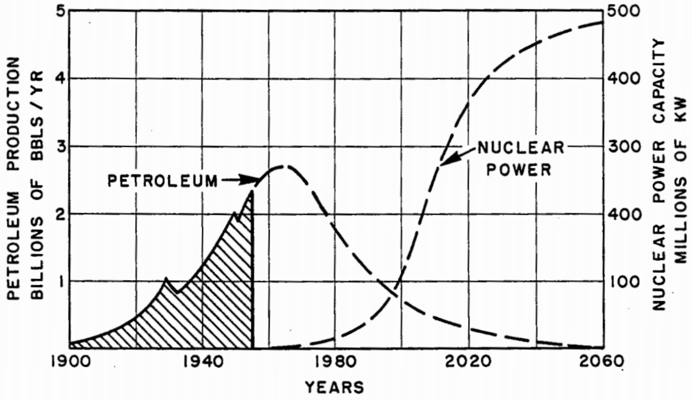


Figure 29 – Concurrent decline of petroleum production and rise of production of nuclear power in the United States. Growth rate of 10 percent per year for nuclear power is assumed; actual rate may be twice this amount.

- Possible scenario projected from 1956 by US geologist M. King Hubbert
- Oil production in the US did indeed peak in the 1970s, but returned to peak height in last decade thanks to shale oil extraction with fracking
- Nuclear expanded but plateaued
- **What might we be getting wrong in the 2020s?**

Source: Hubbert, 1956

We should be skeptical about models and modellers

Models can:

- **under- or overestimate rates of change** (e.g. under: PV uptake, over: onshore wind in UK/Germany/Netherlands)
- **underestimate social factors** (e.g. concern about nuclear / transmission / wind)
- **extrapolate based on uncertain data** (e.g. oil reserves, learning curves for PV)
- **focus on easy-to-solve rather than policy-relevant problems** (e.g. most research)
- **neglect uncertainty** (e.g. in short-term due to weather forecasts, or in long-term due to cost, political uncertainty and technological development)
- **neglect need for robustness** (e.g. securing energy system against contingencies, attack)
- **neglect complex interactions of markets and incentive structures** (e.g. abuse of market power, non-linearities not represented in models, lumpiness, etc.)
- **neglect non-linearities and non-convexities** (e.g. power flow, or also learning curves, behavioural effects, perverse local optima, many, many more)

Robustness to Different Weather Years

Different Weather Years

Many of the simulations we looked at in this course, and many in the literature, used single weather years to determine optimal investments.

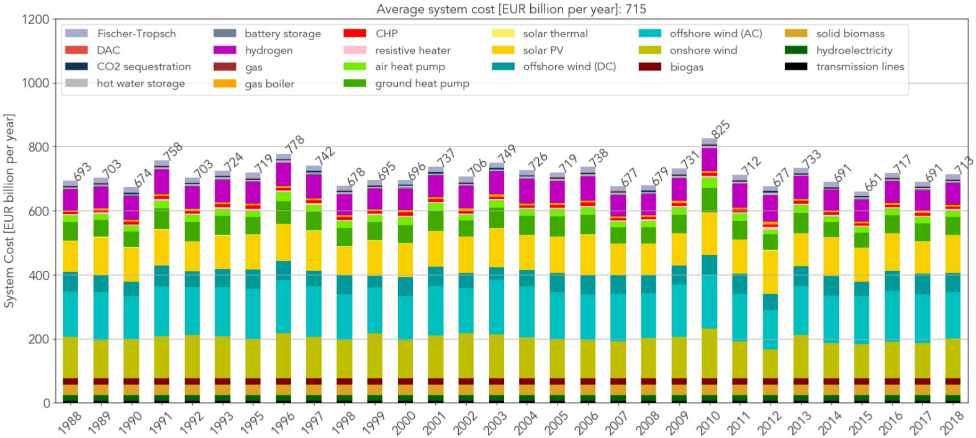
This is problematic since:

- Weather changes from year to year
- There are decadal variations of wind
- Demand changes (particularly space heating demand during cold years)

But computing investments against 30 years of data (262,800 hours) is not feasible.

Different Weather Years

If we use different weather years to optimize sector-coupled European model with net-zero CO_2 emissions (including industry) we see broadly stable technology choices but variations in total system costs of up to 20%. NB: In real world cannot reoptimize investment every year!



Source: Lin Yang MA thesis

Different Weather Years

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Biggest changes are driven by space heating demand. Cold years (like 2010) are more expensive.

Source: Lin Yang MA thesis

Different Weather Years

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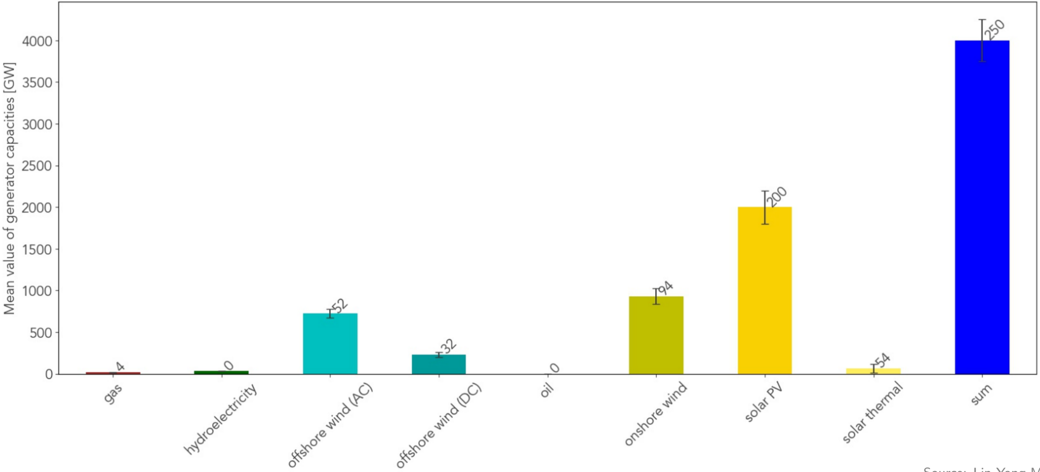
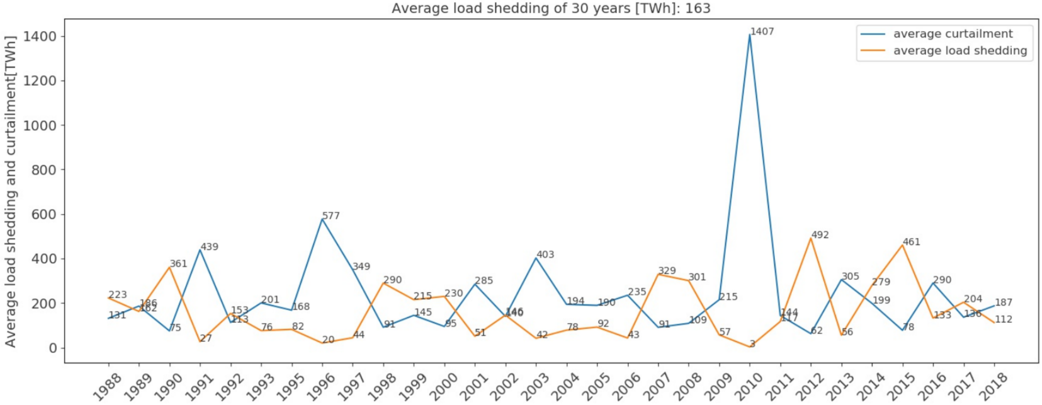
Optimal technology investments do not change dramatically from year to year. Here we show the mean capacities with standard deviation.



Source: Lin Yang MA thesis

Different Weather Years

If we fix the optimal technology investments based on the weather of one year (x-axis), then run the dispatch over all 30 years (900 simulations in total), we can assess average curtailment and load-shedding. Using coldest year 2010 gives low load-shedding but high curtailment.



Source: Lin Yang MA thesis

Using 2010 investments

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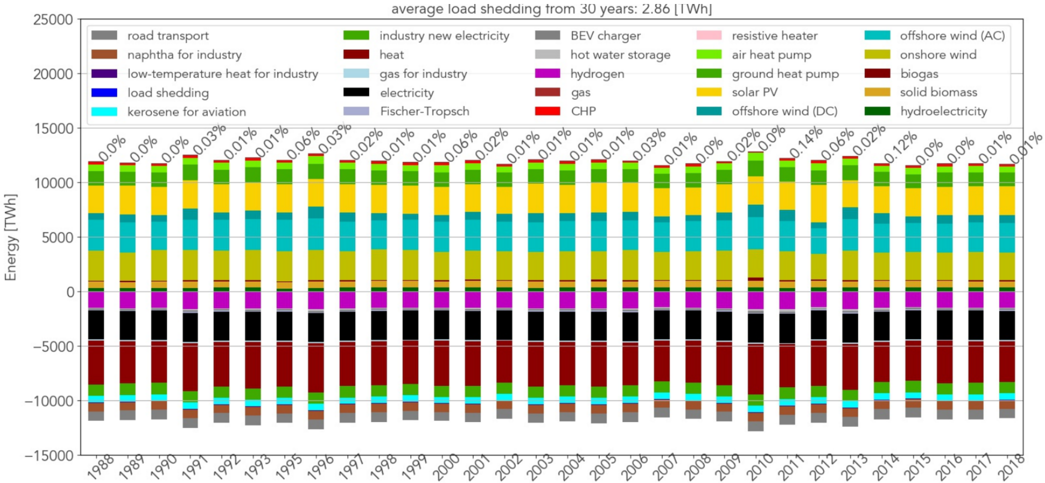
Using coldest year 2010 guarantees virtually no load-shedding in entire 30 years, but leads to excess energy in most years. Better to store excess energy from warmer years (e.g. chemically).



Source: Lin Yang MA thesis

Effects of Climate Change on Energy System

Climate change

- What are the consequences of climate change for highly renewable energy systems?
- How will generation patterns for wind and solar change?
- What will be the effects on the dimensioning of wind, solar, storage, networks and backup generation?

Climate change scenarios: RCP 8.5

Take a simulated dataset of how the weather would look between today and the year 2100 with a scenario of high concentrations of greenhouse gases.

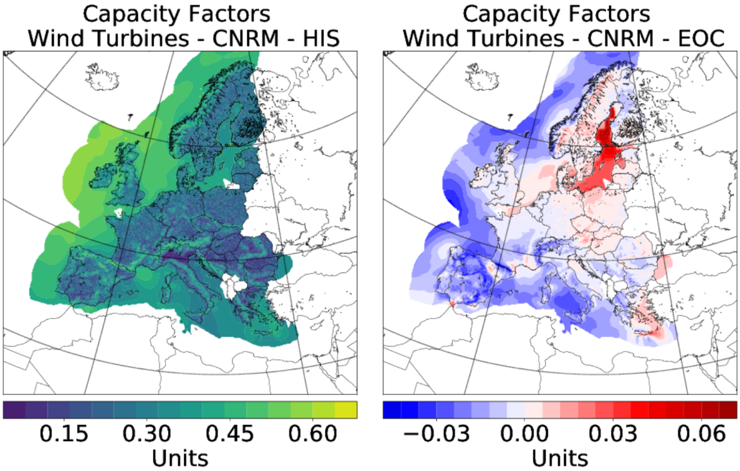
The scenario is called Representative Concentration Pathways 8.5 (RCP 8.5), since it estimates a radiative forcing of $\Delta P = 8.5 \ \mathrm{W/m^2}$ (difference between insolation and energy radiated into space) at the end of the century. It is a **worst-case scenario** and extrapolates current greenhouse gas emissions without reduction efforts (improbable given current trajectories of coal, renewables and EVs). This corresponds to a CO_2-equivalent-concentration (including all forcing agents) of approximately 1250 ppm (today around 410 pmm for CO_2) and an average temperature increase of $\Delta T = 3.7 \pm 1.1$ C at the end of the century, dependent on the model used.

Compare historical values (HIS) to begin/middle/end of the century (B/M/EOC).

Changes to wind capacity factors

Left: historic (HIS) wind capacity factors 1970-2005

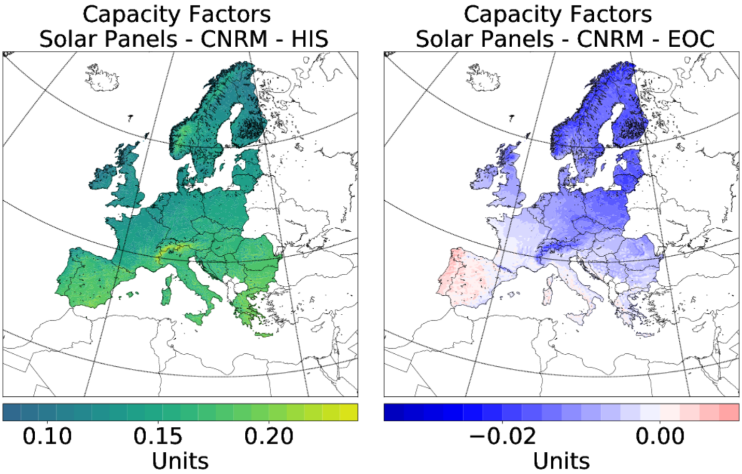
Right: change at end of century (EOC) 2070-2100



- Small ($\sim 5\%$) average increase in Northern Europe
- Small ($\sim 5\%$) average decrease in Southern Europe

Source: Schlott et al, 2018

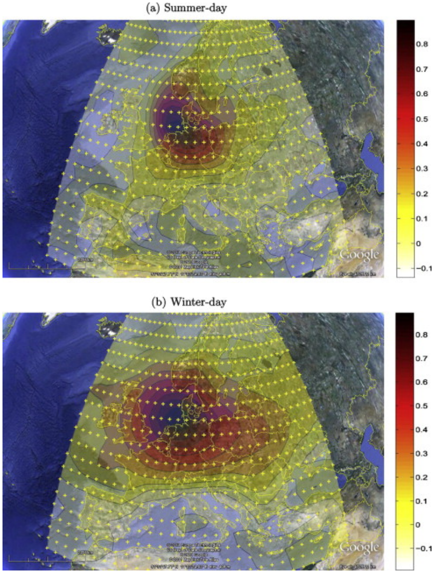
Changes to solar capacity factors



- Small (∼ 5%) increase in in Southern Europe around Mediterranean
- Smallish (∼ 10%) decrease in Northern Europe (due to increased cloud cover)
- Solar results known to be a little unreliable because of cloud modelling etc.

Source: Schlott et al, 2018

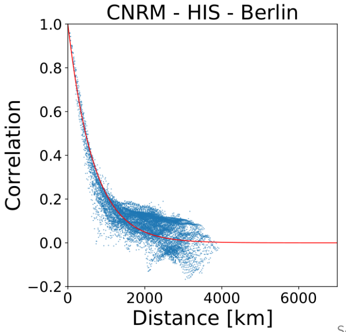
Correlation Length



The Pearson correlation coefficient of wind time series with a point in northern Germany decays exponentially with distance. Determine the **correlation length** L by fitting the function:

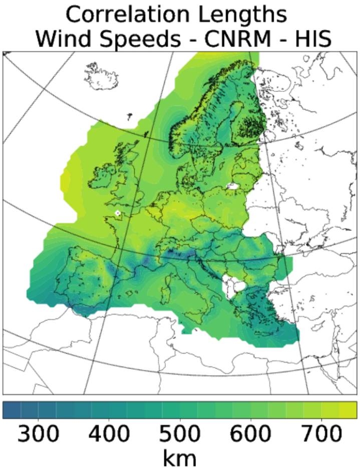
$$\rho \sim e^{-\frac{x}{L}}$$

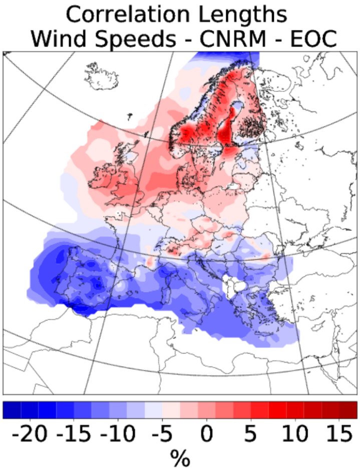
to the radial decay with distance x.



Source: Hagspiel et al, 2012

Changes to wind speed correlation lengths





- Correlation lengths are longer in the North than the South because of big weather systems that roll in from the Atlantic to the North (in the South they get dissipated).
- With global warming, correlation lengths grow longer in the North and shorter in the South.
- This is because weather systems have more energy and are bigger in the North.

Source: Schlott et al, 2018

Effects of climate change on power system

Conclusions from study of effects on the power system:

- Most effects are small ($\sim 5-10\%$); total system costs increase by only 5%.
- Longer correlation lengths see greater benefit from continental transmission.
- Impact of climate change is of a similar magnitude to the uncertainty between the different weather models.
- Not considered: Space heating and cooling demand changes may have bigger effect on overall energy system.
- Not considered: Impact of extreme weather events (storms, fires, droughts).

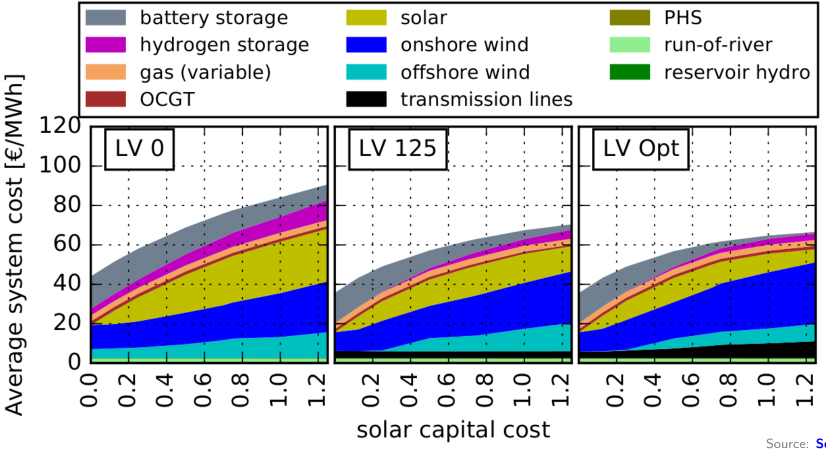
For more results, see 'The Impact of Climate Change on a Cost-Optimal Highly Renewable European Electricity Network,' **https://arxiv.org/abs/1805.11673**

Cost and Political Uncertainty

Power System Model: Sensitivity to Changing Solar Cost

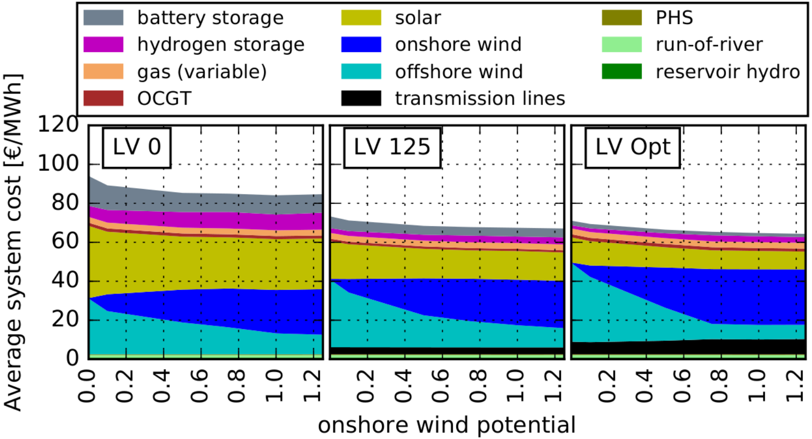
In 30-node European electricity system with 95% CO_2 reduction, change solar capital cost relative to default. NB: Even at zero solar cost, there is still wind. Why? Seasonality.

LV 0: No cross-border grid, LV 125: compromise grid, LV Opt: optimal grid.



Source: Schlachtberger et al, 2018

In electricity system with 95% CO_2 reduction, reduce installable potential for onshore wind. Onshore substituted with offshore at only small extra system cost. BUT assumes sufficient grid capacity within each country to get offshore from coast to load.



Source: Schlachtberger et al, 2018

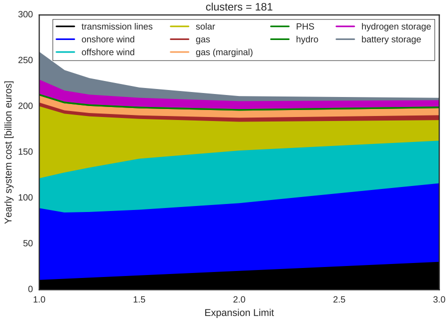
Sensitivity of Optimisation to Cost, Weather Data and Policy Constraints

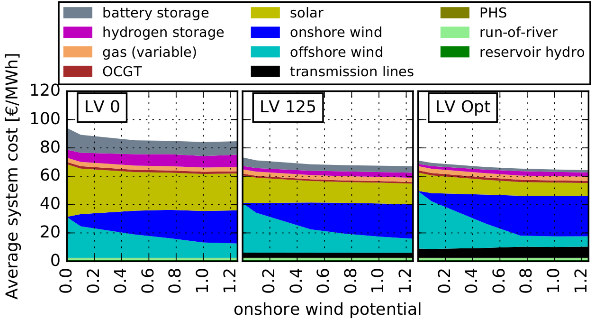
See Schlachtberger et al, 'Cost optimal scenarios of a future highly renewable European electricity system: Exploring the influence of weather data, cost parameters and policy constraints,' 2018, **https://arxiv.org/abs/1803.09711**

Near-Optimal Energy Systems

Both for changing transmission expansion AND onshore wind installable potentials, we've seen that total system costs are **flat around the optimum**.

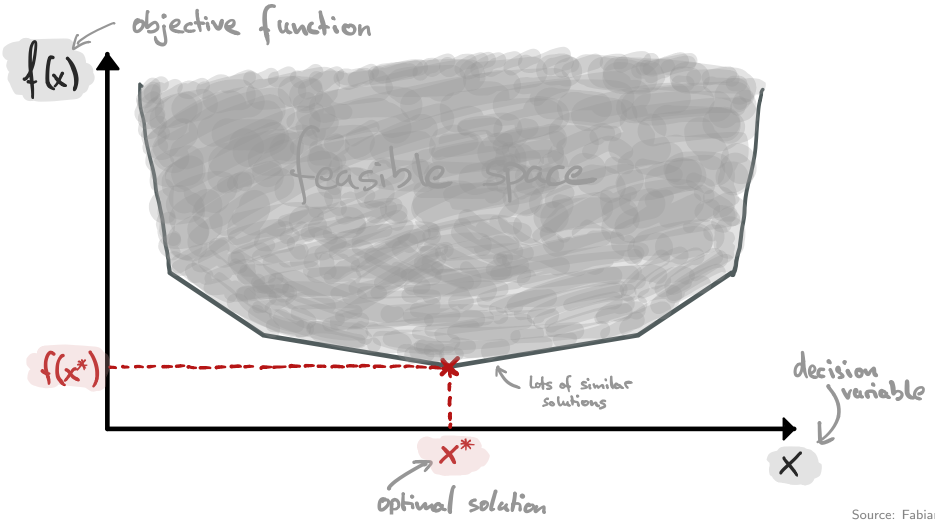
Can we explore this **near-optimal space** more systematically?





Large Space of Near-Optimal Energy Systems

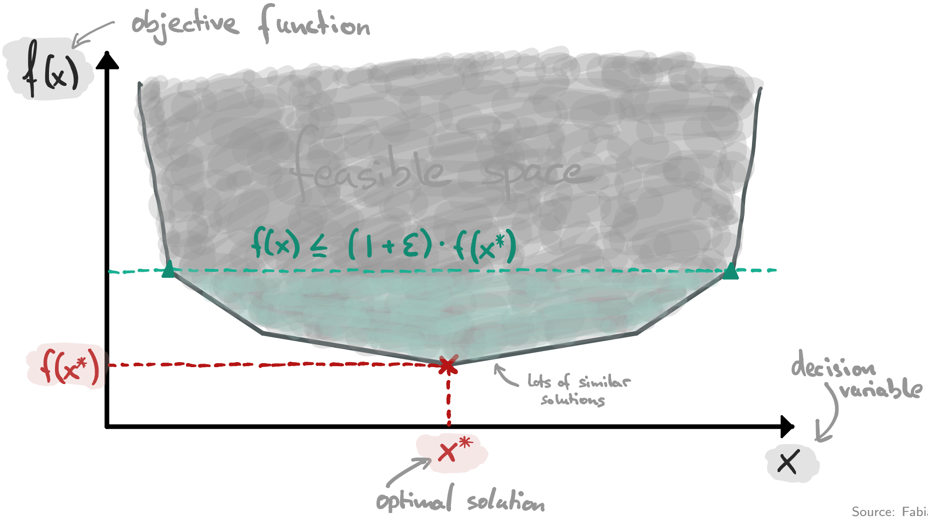
There is a **large degeneracy** of different possible energy systems close to the optimum.



Source: Fabian Neumann

Large Space of Near-Optimal Energy Systems

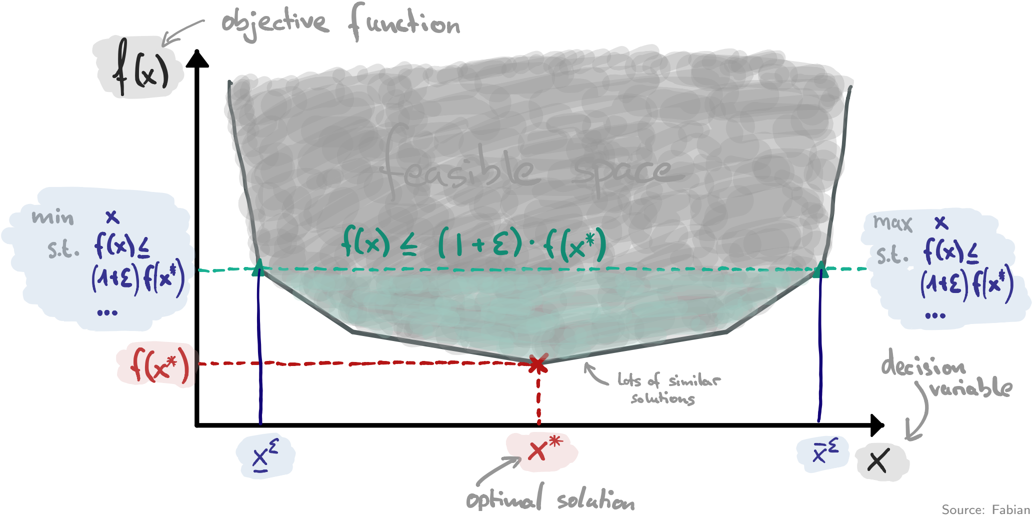
Consider the part of the feasible space within ε of the optimum $f(x^*)$.



Source: Fabian Neumann

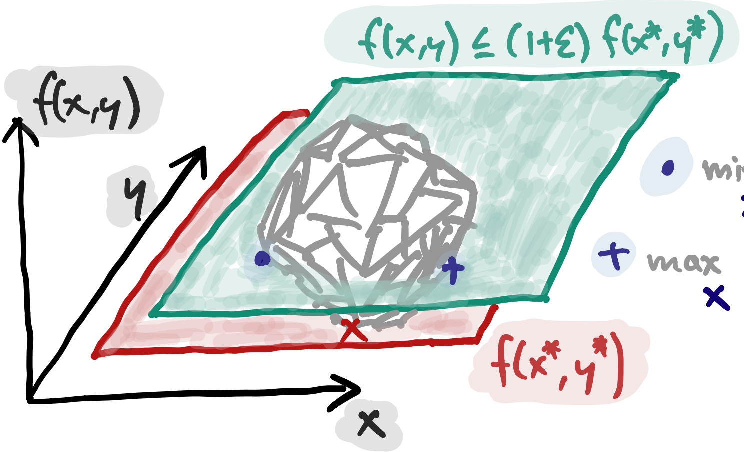
Large Space of Near-Optimal Energy Systems

Now within ε of the optimum $f(x^*)$, try minimising or maximising x, to probe space.



Source: Fabian Neumann

NB: Decision space of variables is multi-dimensional, so can probe only one direction at a time.



Source: Fabian Neumann

Apply this technique to a 100-node model of the European electricity with 100% renewable energy.

1. Find the **least-cost power system**.
2. For $\varepsilon \in \{0.5, 1, \dots, 10\}\%$ **minimise/maximise** investment in
   - generation capacity (onshore and/or offshore wind, solar),
   - storage capacity (hydrogen, batteries, total storage) and
   - transmission volume (HVAC lines and HVDC links)

   such that **total annual system costs increase by less than ε**.

Methodology adapted from Method to Generate Alternatives (MGA) but 'alternatives' are forced in politically-interesting directions.

Source: Fabian Neumann

Example: 100% renewable electricity system for Europe

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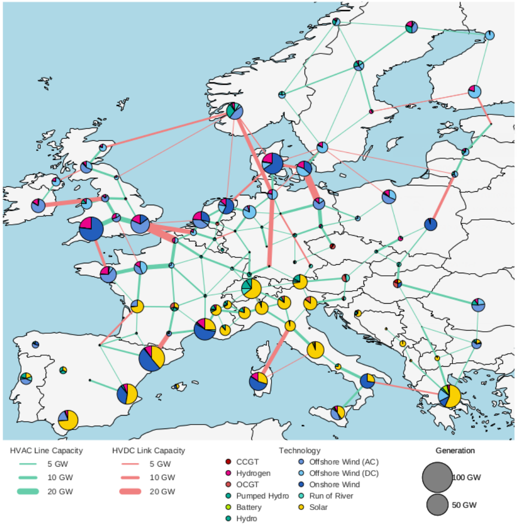
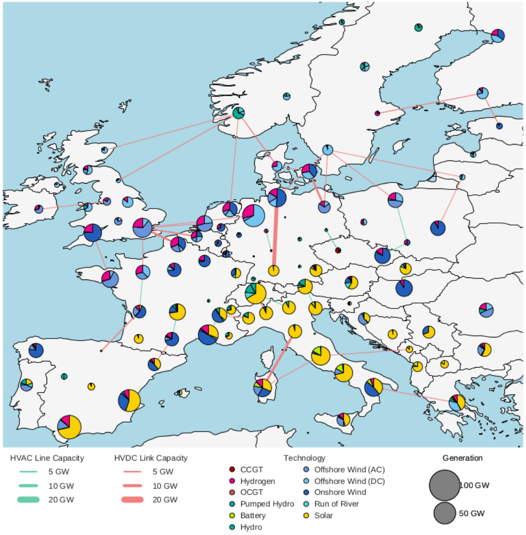
Capacity expansion in optimum:

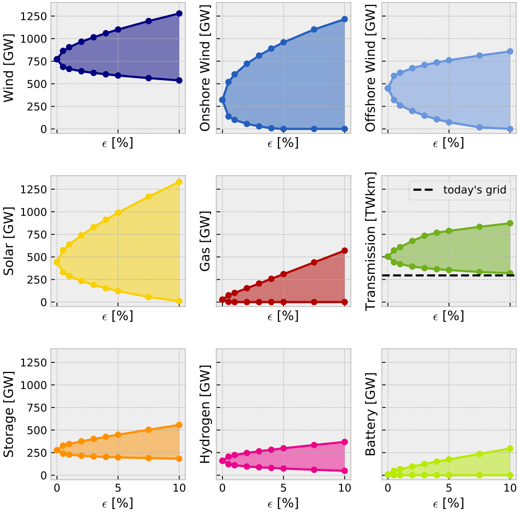


$\varepsilon = 10\%$ above optimum, minimise new grid:



Source: Neumann & Brown, 2020

Example: 100% renewable electricity system for Europe



Within 10% of the optimum we can:

- Eliminate most grid expansion
- Exclude onshore or offshore wind or PV
- Exclude battery or most hydrogen storage

Robust conclusions: wind, some transmission, some storage, preferably hydrogen storage, required for a cost-effective solution.

This gives space to choose solutions with **higher public acceptance**.

Source: Neumann & Brown, 2020

Flat directions allow society to choose based on other criteria

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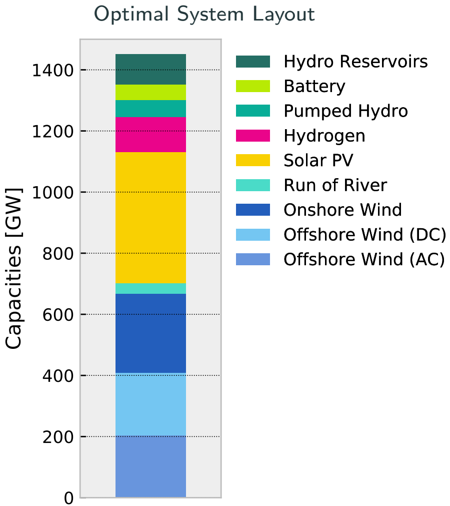
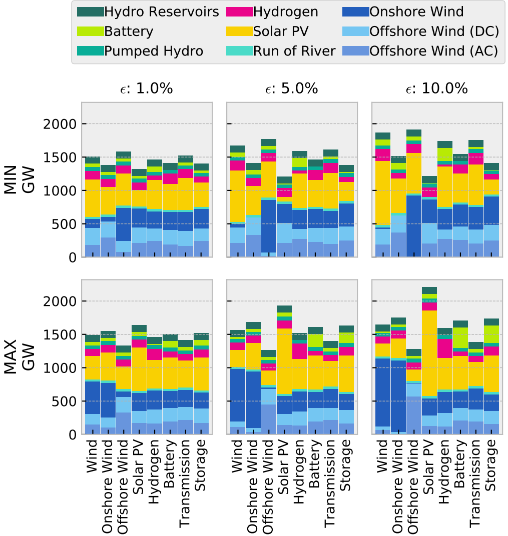
This flatness may allow us to choose solutions with **higher public acceptance** at only **small extra cost**.

These trade-offs will occupy us for the next 30 years!

Dependencies: Extremes cannot be achieved simultaneously





Near-Optimal Systems: Conclusions

- Optimizing a single model gives a **false sense of exactness**.
- There are many uncertainties about cost assumptions and political targets.
- There are also **structural model uncertainties** since the feasible space can be very **flat** near the optimum, such that the solution chosen is random within flat area.
- We can use these techniques to probe the **near-optimal space**.
- This gives us fuzzier but **more robust** conclusions (e.g. need wind, some transmission and some long-term storage for a cost-effective solution).
- It also allows us to find cost-effective solutions with **higher public acceptance**.

More details: Fabian Neumann, Tom Brown, "The Near-Optimal Feasible Space of a Renewable Power System Model," 2020, EPSR, **https://arxiv.org/abs/1910.01891**.